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Adaptive Neuro-Fuzzy Inference System for mid term prognostic error stabilization

Otilia DRAGOMIR, Rafael GOURIVEAU, Nouredine ZERHOUNI

Abstract

The high costs in maintaining complex equipments make necessary to enhance maintenance support systems and industrial and research communities take a growing interest in the “prognostic process”. However, this activity is still not well bounded and real prognostic systems are scarce. Thus, the general purpose of the paper is to explore the way of performing failure prognostics so that manager can act consequently. The prognostic process is discussed from different points of view (concept, metrics, approaches and tools) in order to point out the pragmatic challenges of this activity. Assuming that maintenance decisions follow from a prediction step, the stabilization of mid term prediction errors appears to be essential. For that purpose a neuro-fuzzy predictor based on the ANFIS model is proposed to perform prognostic.

Keywords: prognostic, neuro-fuzzy system, ANFIS, error of prediction.

1 Introduction

Maintenance activity combines different methods, tools and techniques to reduce costs while increasing availability, reliability and security of equipments. That said, maintenance is far away to be only an industrial area of interest and researchers also show a growing attention to this thematic.

The initial maintenance framework was delimited by the necessity of “perceiving” phenomena, next, of “understanding” them, and finally, of “acting” consequently. However, rather than understanding a phenomenon which has just appeared like a failure, it seems convenient to “anticipate” it’s manifestation in order to act consequently and resort to protective actions. This is what could be defined as the “prognostic process”. Prognostic is nowadays recognized as a key feature in maintenance strategies. However, real prognostic systems are scarce in industry and that can be explained from different aspects. Firstly, prognostic still is not a stabilized concept: there is no consensual way of understanding it which makes harder the definition of tools to support it in real applications. Secondly, many approaches for prediction exist whose applicability is highly dependent of the available knowledge on the monitored system. Thirdly, the vagueness of prognostic process definition impedes to point out the inherent challenges for scientists. Thus, the purpose of this paper is to analyze and discuss the prognostic process from different points of view, and to propose a way of handling failure prognostics so that practitioners can act consequently.

The paper is organized in two parts. First, the prognostic framework is delimited, starting with the prognostic definition, metrics, approaches and tools. Considering prognostic as the association of a prediction and an evaluation steps, a classification of prognostic metrics is given. The whole aims at giving a frame to perform (and develop) real prognostic systems. In the second section, the use of neuro-fuzzy predictor for prognostic purpose is briefly justified and an illustration based on the adaptive neuro-fuzzy inference system is given. The proposed system performs “good” prediction and is built in order to reach the stabilization of mid term prognostic errors.

2 Performing prognostic: concept, measures and tools

2.1 Prognostic concept

Although there are some divergences in literature (see [2]), prognostic can be defined as proposed by the International Organization for Standardization: “prognostic is the estimation of time to failure and risk for one or more existing and future failure modes” [4]. In this acceptance, prognostic is also called the “prediction of a system’s lifetime” as it is a process whose objective is to predict the remaining useful life (RUL) before a failure occurs given the current machine condition and past operation profile [6]. Two salient characteristics of prognostic can be pointed out [2]. 1) Prognostic is mostly assimilated to a prediction process (a future situation must be caught). 2) Prognostic is grounded on the failure notion, which implies that it is associated with a degree of acceptability (the predicted situation must be assessed with regard to a referential). Therby, at a prediction level, a prognostic system should be able to determine the future state of equipment as closely as possible to the future real state. Also, the control of the performance of prediction is the premise of a good global prognostic system. At an evaluation level, the predicted situation should be evaluated regarding the reference levels, RUL, confidence, accuracy, etc., which implies the definition of prognostic measures.

2.2 Prognostic metrics

There is no general agreement as to an appropriate and acceptable set of metrics that can be employed effectively in prognostic applications, and researchers and CBM practitioners are still working on this [7].

1) The main objective of prognostic is to provide the efficient information that enable the underlying decision process, i.e., the choice of maintenance actions. Thus, a first set of metrics are those that quantify the risks incurred by the monitored system. This kind of metrics can be called the **prognostic measures**.

As mentioned earlier, the main prognostic measure pursued is the predicted time to failure (**TTF**), also called the remaining useful life (**RUL**). In addition, a **confidence** measure can be built to indicate the degree of certitude of the future predicted failure time. By extension, and considering that practitioners can be interested on assessing the system with regard to any performance limit, RUL and confidence can be generalized: in Fig. 1(a), **TTxx** refers to the remaining time to overpass the performance limit Perf/xx, and **Conf/xxT** is the confidence with which can be taken the asset $TT_{xx} > T$.

2) Assuming that prognostic is in essence an uncertain process, it is useful to be able to judge from its “quality” in order to imagine more suitable actions. In this way, different indicators can be constructed: the **prognostic system performance measures**.

The **timeliness** of the predicted time to failure (TTF) is the relative position of the probability density function (pdf) of the prediction model along the time axis with respect to the occurrence of the failure event. This measure evolves as more data are available and reveals the expected time to perform preventive actions [7] (see Fig. 1(b)). According to [3], one needs to define two different boundaries for the maximum acceptable late and early predictions.

Accuracy measures the closeness of the predicted value to the actual value. It has an exponential form and is as higher as the error between the predicted value of TTF and the real one is smaller.

Precision measure reveals how close predictions are grouped or clustered together and is a measure of the narrowness of the interval in which the remaining life falls. Precision follows from the variance of the predicted results for many experiments. The complementarity of accuracy and precision is illustrated in Fig. 1(c).

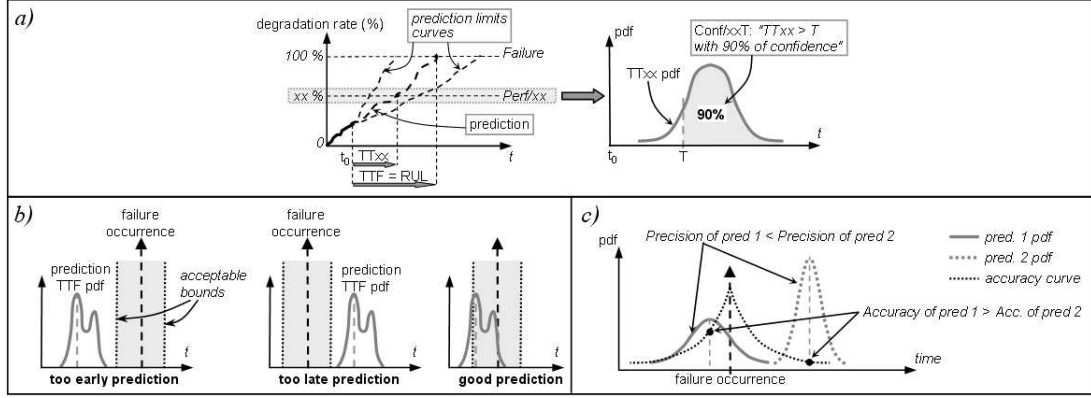


Figure 1: Metrics - (a) RUL, TTxx and confidence, (b) timeliness, (c) accuracy and precision

2.3 Prognostic approaches

Various prognostic approaches have been developed ranging in fidelity from simple historical failure rate models to high-fidelity physics-based models [7]. Similarly to diagnosis, prognostic methods can be associated with one of the following two approaches, namely model-based and data-driven.

1) Model-based methods assume that an accurate mathematical model for the analyzed system can be constructed. The main advantage of these approaches is their ability to incorporate physical understanding of monitored system. Moreover, if the understanding of the system degradation improves, the model can be adapted to increase its accuracy and to address subtle performance problems. But, this closed relation with a mathematical model may also be a strong weakness: it can be difficult, even impossible to catch the system's behavior.

2) Data-driven approaches use real data to track, approximate and forecast features revealing the degradation of components; in many applications, measured input/output data is the major source for a deeper understanding of the system degradation. Data-driven approaches can be divided into two categories: statistical techniques (multivariate statistical methods, linear and quadratic discriminators, etc.), and artificial intelligence (AI) techniques (neural networks, fuzzy systems, etc.). The strength of data-driven techniques is their ability to transform high-dimensional noisy data into lower dimensional information for decisions. In practice however, data-driven approaches are highly-dependent on the quantity and quality of operational data.

3 Building a neuro-fuzzy prognostic tool

3.1 ANFIS model: an adequate prediction tool

Real systems are complex and their behavior is often non linear, non stationary. These considerations make harder a modeling step, even impossible. Yet, a prediction computational tool must deal with it. Moreover, monitoring systems have evolved and it is now quite easy to online gather data. According to all this, data-driven approaches have been increasingly applied to machine prognostic. More precisely, works have been led to develop systems that can perform nonlinear modeling without a priori knowledge, and that are able to learn complex relationships among "inputs and outputs" (universal approximators). Indeed, artificial neural networks (ANNs) have been used to support the prediction process. Recent works focus on the interest of hybrid systems: many investigations aim at overcoming the major ANNs drawback (lack of

knowledge explanation) while preserving their learning capability. In this way, neuro-fuzzy systems are well adapted. More precisely, first order Tagaki-Sugeno (TS) fuzzy models have shown improved performances over ANNs and conventional approaches [8]. Thereby, they can perform the degradation modeling step of prognostic.

A particular architecture of TS neuro-fuzzy systems is that of the adaptive neuro-fuzzy inference system (ANFIS) [5]. ANFIS is an inference system in which the parameters associated with specific memberships functions are computed using either a backpropagation gradient descent algorithm alone or in combination with a least squares method. Thanks to its structure and learning capability, ANFIS is fitted to predict irregular or non-periodic time series. However, when used for mid term predictions purpose, ANFIS can make large residual errors. Next part of the paper emphasizes on this aspect.

3.2 Mid term prognostic error stabilization with ANFIS predictor

Since the occurrence of a failure is in essence uncertain, a prognostic tool should be able to make predictions with quite the same accuracy at short, mid and long terms. This is the purpose of this part (assuming that ANFIS is an adequate short term prediction tool).

1) Here, prognostic is considered as a prediction process based on the aggregation of, naturally, past and present states of the system, but also, of the known future ones. Indeed, it appears to be useful to take into account future actions like the modification of the mission profile due to some extern interventions or like the influence of a scheduled maintenance action. Consequently, the just-in-time-point (the time of failure when the life duration is [0%]) gets another dimension related to the starting point ([100%] of machine life duration) (see Fig. 2).

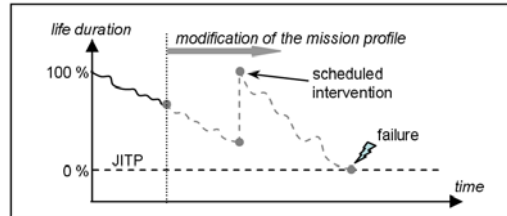


Figure 2: Influence of scheduled maintenance actions on the prediction process

2) In most of the papers in which ANFIS is used as a prediction system, inputs are directly extracted from the data sets. Here, the Box-Jenkins furnace benchmark is used. There are originally 296 data samples $\{y(t), u(t)\}$, from $t=1$ to $t=296$. From the real process, CO2 concentration is considered as the output of the model $y(t)$, and gas flow rate as the input $u(t)$. In order to predict $y(t)$ based on $y(t-1), y(t-2), y(t-3), y(t-4), u(t-1), u(t-2), u(t-3), u(t-4), u(t-5), u(t-6)$, the number of effective data points becomes 290. A selection method must be used because all ten input variables generate too many rules and parameters to be updated on the learning phase: it would make the training data insufficient and would obviously increase the computing time.

3) The choice of an error measure to compare prediction methods has been much discussed (see for example [1]). In any case, error measures are only intended as summaries for the error distribution. This distribution is usually expected to be a normal white noise in a forecasting problem, but it probably is not so in a complex problem like load forecasting. The ANFIS architecture proposed by Jang with two and three selected inputs has satisfactory results for short term predictions. For mid and long terms ones, the obtained errors increase, which affects the prognostic performances (Fig. 3).

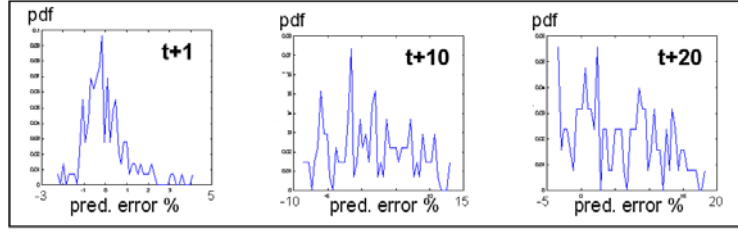


Figure 3: Error of prediction pdf - ANFIS model with two inputs

4) A first way to stabilize the error of prediction is to construct serial architectures of ANFIS models. Indeed, linking two ANFIS enable to take over the growth tendency of error since the second one learns the error of the first one. The effect of this modification is observed on the error values (see Fig. 4). The maximum measured error decreases significantly and becomes satisfactory for mid term predictions as well as the prediction spread does.

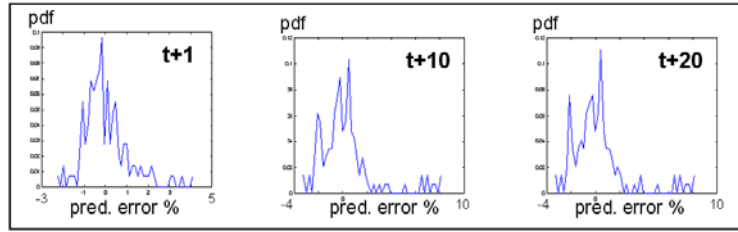


Figure 4: Error of prediction pdf - serial architecture of two ANFIS models with two inputs

5) The known future solicitations of the system (mission profile) can then be injected as input information for the second ANFIS module in the serial architecture. The effect of taking into account the “future” for predictions has also influence over error: the error spreading is significantly reduced and the confidence of the prediction process increases thereby consequently. Mid term predictions reflect the improved quality of the approach (Fig. 5).

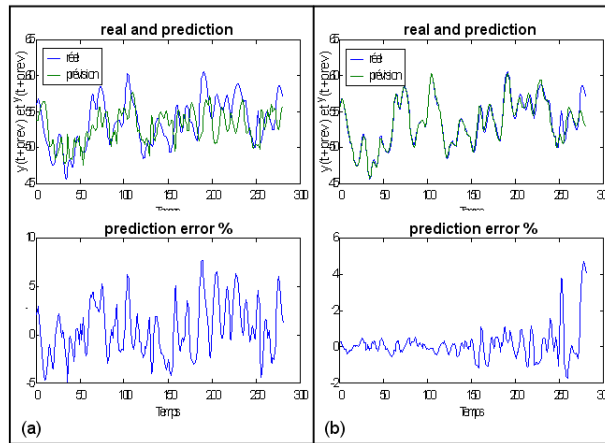


Figure 5: Error of prediction (%) for a serial architecture without (a) and with (b) future known solicitations injection

4 Conclusion and work in progress

In this article, prognostic is presented as the association of a prediction and an evaluation process. Many approaches to support this activity exist, whose applicability and performance must be assessed to develop a prognostic tool. For that purpose, various prognostic metrics exist and are discussed in the paper. All of them are based on the evaluation of the prediction error spreading. Following that, the prediction step of prognostic appears to be a critical one and controlling the performances of predictions is the premise for a good global prognostic system. According to all this, the interest of neuro-fuzzy system is pointed out and a new ANFIS architecture is proposed in order to ensure a certain stability of errors for mid term predictions. The system is based on a serial architecture of various ANFIS models, in order to overcome the local prediction errors (by learning them) and to inject the future scheduled maintenance actions. The obtained results are satisfactory from the industrials point of view since confidence on predictions increases. The work is still in progress and the developments are at present extended in four principal ways. First, the definition of new loss functions in the learning phase is studied. Secondly, the application of ANNs and NFs as tools for a global prognostic is been investigated. Thirdly, the interpretability of the obtained predictive system is been looked in a closely manner. Finally, the implementation of the studied framework is in progress at a French industrial partner for the monitoring of high speed trains motors.

References

- [1] J.G. De Gooijer, R.J. Hyndman, “25 years of time series forecasting”, *International Journal of Forecasting*, Vol. 22, pp. 423-473, 2006.
- [2] O. Dragomir, R. Gouriveau, N. Zerhouni, “Framework for a distributed and hybrid prognostic system”, *In 4th IFAC Conference on Management and Control of Production and Logistics*, 2007.
- [3] K. Goebel, P. Bonissone, “Prognostic information fusion for constant load systems”, *In: Proceedings of 7th annual Conference on Fusion*, Vol. 2, pp. 1247-1255, 2005.
- [4] ISO 13381-1, *Condition monitoring and diagnostics of machines - prognostics - Part1: General guidelines*, International Standard, ISO, 2004.
- [5] J-S.R. Jang and C. Sun, “Neuro-fuzzy modeling and control”, *In: IEEE Proceedings*, Vol. 83, pp. 378-406, 1995.
- [6] A.K.S. Jardine, D. Lin and D. Banjevic, “A review on machinery diagnostics and prognostics implementing condition-based maintenance”, *Mech. Syst. and Sig. Process.*, Vol. 20, pp. 1483-1510, 2006.
- [7] G. Vachtsevanos, F.L. Lewis, M. Roemer, A. Hess and B. Wu, *Intelligent Fault Diagnosis and Prognostic for Engineering System*, New-Jersey, Hoboken: Wiley and Sons, 2006.
- [8] W-Q. Wang, M.F. Goldnaraghi, and F. Ismail, “Prognosis of machine health condition using neuro-fuzzy systems”, *Mech. Syst. and Sig. Process.*, Vol. 18, pp. 813-831, 2004.

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